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Development of a Fuzzy Logic Based Rainfall Prediction Model

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ABSTRACT

The present study investigates the ability of fuzzy rules/logic in modeling rainfall for South Western Nigeria. The developed Fuzzy Logic model is made up of two functional components; the knowledge base and the fuzzy reasoning or decision-making unit. Two operations were performed on the Fuzzy Logic model; the fuzzification operation and defuzzification operation. The model predicted outputs were compared with the actual rainfall data. Simulation results reveal that predicted results are in good agreement with measured data. Prediction Error, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Prediction Accuracy were calculated, and on the basis of the results obtained, it can be suggested that fuzzy methodology is efficiently capable of handling scattered data. The developed fuzzy rule-based model shows flexibility and ability in modeling an ill-defined relationship between input and output variables.

Keywords: *Fuzzy rule-based, Knowledge base, Fuzzy reasoning, Fuzzification, Defuzzification.*

1. INTRODUCTION

The tendency to discover unknown aspects of different phenomena has occupied human being's mind from time immemorial. Rather than being a matter of curiosity, forecasting is admired to be used as a basis to perform indispensable preparedness for an upcoming event. In its early ages and as a superstitious concept, forecasting was prematurely aimed to reinforce human against the unpleasant natural catastrophes and is concerned as a scientific capability with a wide range of applications and a variety of purposes.

Weather forecasting is one of the most imperative and demanding operational responsibilities carried out by meteorological services all over the world. It is a complicated procedure that includes numerous specialized fields of know-how (Guhathakurata, 2006). Amongst all weather happenings, rainfall plays the most imperative role in human life. Human civilization to a great extent depends upon its frequency and amount to various scales.

Rainfall is a stochastic process, whose upcoming event depends on some precursors from other parameters such as the sea surface temperature for monthly to seasonal time scales, the surface pressure for weekly to daily time scale and other atmospheric parameters for daily to hourly time scale. The latter atmospheric parameters could be temperature, relative humidity and winds. Variability of weather and climatic factors, especially those atmospheric parameters will be the major force for daily precipitation event. If variability pattern could be recognized and used for future trajectory, daily rainfall prediction is very much feasible. (Edvin and Yudha, 2008)

Several stochastic models have been attempted to forecast the occurrence of rainfall, to investigate its seasonal variability and to forecast monthly/ yearly rainfall over some given geographical area. Daily precipitation occurrence has been viewed through Markov chain by (Chin, 1977). Gregory et al (1993) applied a chain-dependent stochastic model, named as Markov chain model to investigate inter annual variability of area average total precipitation. Wilks (1998) applied mixed exponential distribution to simulate precipitation amount at multiple sites exhibiting realistic spatial correlation.

In this research work, the focus is on the development of fuzzy logic model for predicting rainfall in South-western Nigeria.

2. RELATED WORKS

Rainfall forecasts have significant value for resources planning and management e.g., reservoir operations, agricultural practices and flood emergency responses. To mitigate this, effective planning and management of water resources is necessary. In the short term, this requires a good idea of the upcoming season. In the long term, it needs realistic projections of scenarios of future variability and change (Abraham *et al*., 2001).

Karamouz *et al*. (2004) used a model based on fuzzy rules and **neural networks** using large-scale climatic signals to predict rainfall in the western Iran (the basins of Karoon, Karkheh and the western border). Their results showed that except for the southwest region, where both models had similar errors of above 35%, in the northwest and the western regions, the error of the fuzzy model was 8.4%; that is, 13% lower than that of neural network.

Halide and Ridd (2002) used **fuzzy logic** to rainfall prediction. The **fuzzy logic** technique is used to model and predict local rainfall data. The RMSE between data and model output is found to be 319.0 mm which is smaller than that by using either the local rain or the Niño 3.4 alone of 349.2 and 1557.3 mm, respectively.

Wong *et al*. (2003) constructed fuzzy rule bases with the aid of SOM and back propagation **neural network**s and then with the help of the rule base developed predictive model for rainfall over Switzerland using spatial interpolation.
Bardossy *et al*. (1995) implemented **fuzzy logic** in classifying atmospheric circulation patterns. Özelkan *et al*. (1996) compared the performance of regression analysis and **fuzzy logic** in studying the relationship between monthly atmospheric circulation patterns and precipitation. Pesti *et al*. (1996) implemented **fuzzy logic** in drought assessment. Baum *et al*. (1997) developed cloud classification model using **fuzzy logic**.

Fujibe (1989) classified the pattern of precipitation at Honshu with fuzzy C-means method. Galambosi *et al*. (1999) investigated the effect of ENSO and macro circulation patterns on precipitation at Arizona using Fuzzy Logic. Vivekanandan *et al*. (1999) developed and implemented a **fuzzy logic** algorithm for hydrometeor particle identification that is simple and efficient enough to run in real time for operational use.

Hansen (2003) applied fuzzy k-nn weather prediction system to improve the technique of persistence climatology by past and present weather cases. Shao (2000) established fuzzy **membership function**s, based on cloud amount, cloud type, **wind speed** and relative humidity, to compose a fuzzy function of weather categorization for thermal mapping.

Liu and Chandrasekar (2000) developed a **fuzzy logic** and neuro-fuzzy system for classification of hydrometeor type based on polar metric radar measurements, where **fuzzy logic** was used to infer hydrometeor type and the **neural network**-learning algorithm was used for automatic adjustment of the parameters of the fuzzy sets in the **fuzzy logic** system according to prior knowledge.

Suwardi *et al*. (2006) have used of a neuro-fuzzy system for modeling wet season tropical rainfall. The models resulted low values of the RMSE indicated that the prediction models are reliable in representing the recent inter-annual variation of the wet season tropical rainfall.

3. FUZZY LOGIC

In classical models variables have real number values, the relationships are defined in terms of mathematical functions and the outputs are crisp numerical values (Center and Verma, 1998). In crisp sets, which are collection of objects with the same properties, the objects either belong to the set or not. In practice, the characteristics value for an object belonging to the set is coded as 1 and if it is outside the set then the coding is 0. The key idea in **fuzzy logic** is the allowance of partial belongings of any object to different subsets of the universal set instead of belonging to a single set completely (Center and Verma, 1998).

In **fuzzy logic**, values of variables are expressed by linguistic terms, the relationship is defined in terms of IF-THEN rules and the outputs are also fuzzy subsets which can be made crisp using defuzzification techniques. First the crisp values of system variables are fuzzified to express them in linguistic terms. Fuzzification is a method for determining the degree of membership that a value has to a particular fuzzy set. This is determined by evaluating the **membership function** of the fuzzy set for the value (Center and Verma, 1998).

The origin of the fuzzy logic approach dates back to 1965 since Lotfi Zadeh's introduction of the fuzzy-set theory and its applications. Since then the fuzzy logic concept has found a very wide range of applications especially in the industrial systems control (Hirota, 1993). Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is robust and approximate rather brittle and exact. In contrast with "crisp logic", where binary sets have two-valued logic, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1.(Novák et al., 1999) Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

Fuzzy Logic is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. Fuzzy logic provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information.

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision. Because of its multidisciplinary nature, fuzzy inference systems are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simply (and ambiguously) fuzzy systems.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Lotfi Zadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes. Although the inference process described in the next few sections differs somewhat from the methods described in the original paper, the basic idea is much the same.

Mamdani-type inference, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It is possible, and in many cases much more efficient, to use a single spike as the output membership functions rather than a distributed fuzzy set. This type of output is sometimes known as a *singleton* output membership function, and it can be thought of as a pre-defuzzified fuzzy set. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. Rather than integrating across the two-dimensional function to find the centroid, the weighted average of a few data points are used.

4. DATA AND AREA OF STUDY

Nigeria is located in western Africa on the Gulf of Guinea and has a total area of 923,768 km² (356,669 mi²), making it the world's 32nd-largest country (after Tanzania). It is comparable in size to Venezuela, and is about twice the size of California. It shares a 4047 km (2515-mile) border with Benin (773 km), Niger (1497 km), Chad (87 km), Cameroon (1690 km), and has a coastline of at least 853 km.[28] The highest point in Nigeria is Chappal Waddi at 2,419 m (7,936 feet). Nigeria has a varied landscape. From the Obudu Hills in the southeast through the beaches in the south, the rainforest, the Lagos estuary and savannah in the middle and southwest of the country and the Sahel to the encroaching Sahara in the extreme north. Nigeria's main rivers are the Niger and the Benue which converge and empty into the Niger Delta, the world's largest river deltas. Nigeria is also an important centre for biodiversity. It is widely believed that the areas surrounding Calabar, Cross River State, contain the world's largest diversity of butterflies. The drill monkey is only found in the wild in Southeast Nigeria and neighboring Cameroon.
The study area is Akure, the capital city of Ondo state, which is one of the states in Nigeria where the climate is influenced mainly by the rain-bearing southwest monsoon winds from the ocean and the dry northwest winds from the Sahara Desert. The climatic condition of Akure follows the pattern of south western temperatures and high humidity also characterizes the climate. There are two distinct seasons, the rainy and dry seasons. The rainy season lasts for about seven months (April to October). The rainfall is about 1524mm per year. The atmospheric temperature ranges between 28°C and 31°C and a mean annual relative humidity of about 80 per cent (Ajibefun, 2010).

Fig.1: Map of Nigeria; attribution - Igbekele Ajibefun at *en.wikipedia.org/wiki/Akure*

The data used in this research was collected from a weather station, which consists of many in-situ atmospheric surface parameters such as the precipitation amount, relative humidity, temperature, dew point, wind speed and surface pressure.

5. FUZZY LOGIC MODELING OF RAINFALL PREDICTION SYSTEM

A fuzzy logic model is also known as a fuzzy inference system or fuzzy controller. The fuzzy logic model adopted in this work composed of two functional components. One is the knowledge base, which contains a number of fuzzy if–then rules and a database to define the membership functions of the fuzzy sets used in the fuzzy rules. Based on this knowledge base, the second component is the fuzzy reasoning or decision-making unit to perform the inference operations on the rules.

Two operations are performed for fuzzy logic modeling. When data are ready, a fuzzification operation is processed to compare the input variables with the membership functions on the premise part to obtain the membership values of each linguistic fuzzy set. These membership values from the premise part are combined through a min operator to get firing strength (weight) of each rule in order to generate a qualified consequent (either fuzzy or crisp) of each rule depending on this firing strength. Then the second operation is the defuzzification to aggregate the qualified consequents to produce a crisp output.

The fuzzy inference engine extracts and evaluates rules from the rule base and produces fuzzy outputs. The fuzzy inference engine presented in Akpan (2011) is studied and adopted for the design of rainfall system.

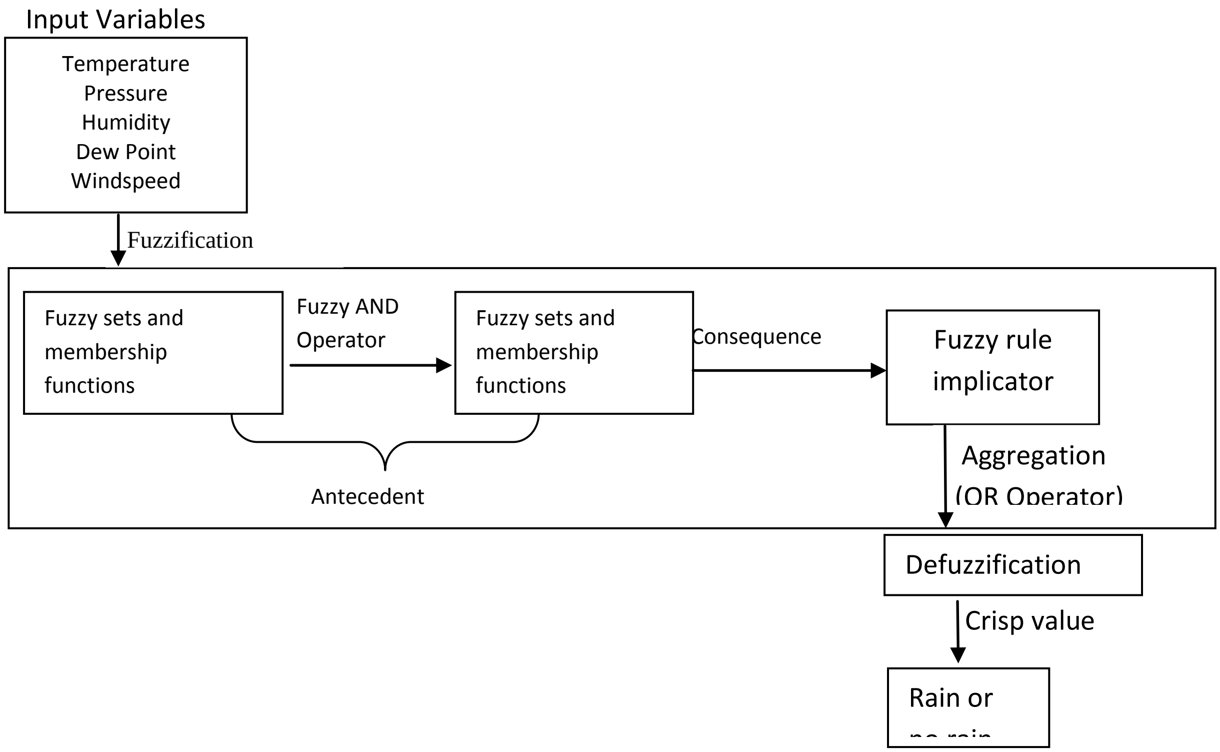

Fig 2: Model of rainfall fuzzy inference procedure

In this work, a small number of linguistic terms (e.g., high, medium, low) referred to as fuzzy sets, are assigned to each variable (e.g., temperature). These fuzzy sets overlap and cover the necessary range of variation for that variable. The degree of membership (from 0 to 1) of a real valued input (e.g., temperature) to a particular fuzzy set A (e.g., high) is given by a membership function $\mu_A(x)$. This transformation of real valued inputs into a degree of membership in a particular fuzzy set is called fuzzification.

Fuzzification of linguistic variables involves: Classification of parameters into linguistic labels and Assigning membership functions for each of the variable.

The five parameters used in this system are: Temperature, Humidity, Dew point, Wind speed and Pressure. Each of these parameters is classified into linguistic labels as shown in table 1.

Table1: Linguistic labels for fuzzy variables

S/No	Parameters	Linguistic Labels
1	Temperature	Very high TM, High TM, Medium TM, Low TM, Very low TM
2	Pressure	Very high PR, High PR, Medium PR, Low PR, Very low PR
3	Humidity	Very high HU, High HU, Medium HU, Low HU, Very low HU
4	Dew Point	Very high DP, High DP, Medium DP, Low DP, Very low DP
5	Wind speed	Very high WS, High WS, Medium WS, Low WS, Very low WS
6	Rain Fall	Very high RF, High RF, Medium RF, Low RF, Very low RF

Table 2: Linguistic values and their ranges

Linguistic Values	**Notations**	**Numerical Ranges**
Very Low	VL	[0, 0.3]
Low	L	[0, 0.4]
Medium	M	[0.3, 0.7]
High	H	[0.4, 0.8]
Very High	VH	[0.7, 1.0]

$$Var(x) = Var(x) = \begin{cases} \text{"VL"} & if\ var(x) < 0\cdot 3 \\ \text{"L"} & if\ 0\cdot 0 \le var(x) < 0.4 \\ \text{"M"} & if\ 0.3 \le var(x) < 0\cdot 7 \\ \text{"H"} & if\ 0\cdot 4 \le var(x) < 0\cdot 8 \\ VH & if\ 0\cdot 7 \le var(x) \le 1.0 \end{cases} \quad (1.0)$$

The linguistic expression for the variables and their membership functions are evaluated from the following triangular membership functions and it is defined by a lower limit **a**, an upper limit **b**, and a value **m**, where **a** < **m** < **b**.

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \frac{x-a}{m-a} & a < x \le m \\ 1, & x \ge b \end{cases} \quad (2.0)$$

The actual membership functions of these linguistic values are given as follows:

$$VL(x) = \begin{cases} 0 & if\ x \le 0 \\ \frac{x}{0\cdot 3} & if\ 0 < x \le 0.3 \\ 1 & if\ x \ge 0\cdot 3 \end{cases} \quad (3.0)$$

$$L(x) = \begin{cases} 0 & if\ x < 0 \\ \frac{x}{0\cdot 4} & if\ 0 \le x < 0.4 \\ 1 & if\ x \ge 0\cdot 4 \end{cases} \quad (4.0)$$

$$M(x) = \begin{cases} 0 & if\ x < 0\cdot 3 \\ \frac{x-0\cdot 4}{0\cdot 4} & if\ 0\cdot 3 \le x < 0.7 \\ 1 & if\ x \ge 0\cdot 7 \end{cases} \quad (5.0)$$

$$H(x) = \begin{cases} 0 & if\ x < 0\cdot 4 \\ \frac{x-0\cdot 4}{0\cdot 4} & if\ 0\cdot 4 \le x < 0.8 \\ 1 & if\ x \ge 0\cdot 8 \end{cases} \quad (6.0)$$

$$VH(x) = \begin{cases} 0 & if\ x \le 0\cdot 7 \\ \frac{x-0\cdot 7}{0\cdot 3} & if\ 0\cdot 7 < x \le 1\cdot 0 \\ 1 & if\ x \ge 1\cdot 0 \end{cases} \quad (7.0)$$

The antecedent and implication approach used in this work follows the Mamdanis reasoning method (Takagi and Sugeno, 1992, Nazmy et al, 2009, Moreno et al, 2007). For instance, suppose we use this rule;

IF (TP is low) and (HU is High) and (DP is Very high) and (WS is High) and (PR is Very low) then (RF is High).

The antecedent is evaluated as follows: Suppose we pick the values as in table 3.2.

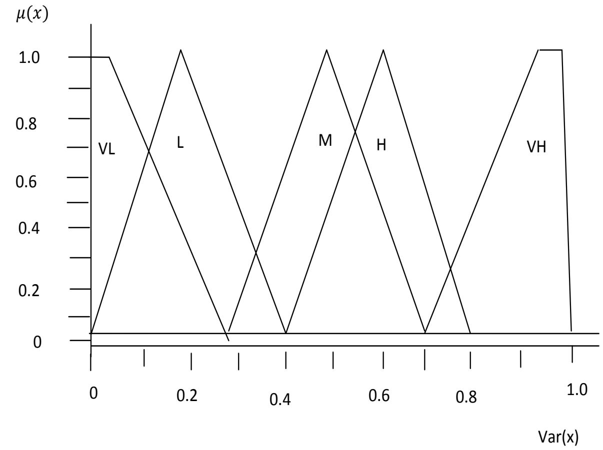

Fig 3: Graph of membership function

Table 3: Values of rainfall parameters and their membership function

Rainfall parameters	Fuzzy set	value(y)	$\mu(y)$
temperature	Low	**0.3**	**0.35**
Humidity	High	**0.7**	**0.76**
Dew point	Very high	**0.9**	**1.0**
Wind speed	High	**0.8**	**0.88**
Pressure	Very low	**0.1**	**0.15**

From the rule definition, the AND operator is used. To evaluate the antecedent, the Mamdani **min** function is applied to determine the firing level (α) of the rule as follows:

$$\boldsymbol{\mu}_{\boldsymbol{A\cap B(y)}} = Min[\boldsymbol{\mu_A}(\mathrm{y}), \boldsymbol{\mu_B}(\mathrm{y})] \mid \mathrm{y} \in Y \quad (8.0)$$

$$\alpha = min\left\{ \begin{matrix} \mu(TO = 0.3), \mu(HU = 0.7), \mu(DP = 0.9) \\ , \mu(WS = 0.8), \mu(PR = 0.1) \end{matrix} \right\}$$

$$= min\left\{ \begin{matrix} \mu_{Low}(0.3), \mu_{high}(0.7), \mu_{very\ high}(0.9), \\ \mu_{high}(0.8), \mu_{very\ low}(0.1) \end{matrix} \right\}$$

$$= min\{0.35, 0.76, 1.0, 0.88, 0.15\} = 0.15$$

The value of the antecedent is multiplied by the weight factor to give a value which represents the degree of support (firing strength) for the rule

$$FV_i = \propto_i w_i \quad (9.0)$$

In this work $w_i = 1$ therefore

$$FV_i = \propto_i \quad (10.0)$$

Firing strength of a rule is represented by the shaded portion of figure 3

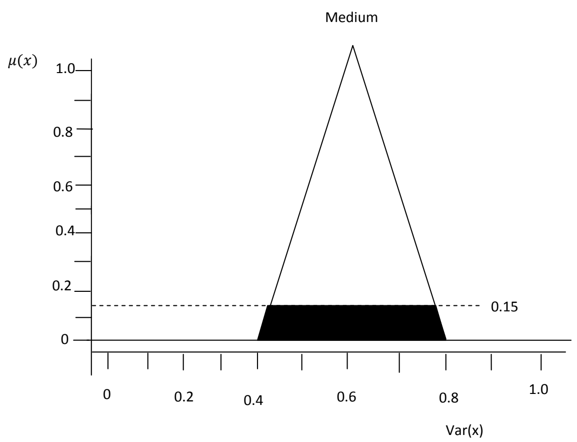

Fig 4: Firing strength of a rule

At the aggregation stage, output fuzzy sets of each rule (produced by implication method) are aggregated to form a single fuzzy set. The fuzzy max function (OR operator) presented in equation 3.15 is used for aggregation.

$$\boldsymbol{\mu}_{\boldsymbol{A \cup B(y)}} = Max[\boldsymbol{\mu_A}(\mathrm{y}), \boldsymbol{\mu_B}(\mathrm{y})] \,\Big|\, \mathrm{y} \in Y \qquad (11.0)$$

Suppose there are N rules for rainfall parameters and the fuzzy implication of each rule is represented as FV. Then FV_i is the fuzzy implication (firing strength) of the ith rule.

where $i = 1,2,3,4, \dots, N$

Thus the final fuzzy value is the result of the aggregation operator

$$FV = \max(FV_1, FV_2, FV_3, \dots, FV_N) \qquad (12.0)$$

This will return the largest value. For example

Max (0.15, 0.3, 0.4, 0.67.0.40)= 0.67

Defuzzification involves conversion of the linguistic variables to numerical or crisp values; this work adopts the centroid defuzzification method described in [Bodea, 2009]. This is given as follows:

$$Z = \frac{\sum_{i=1}^{n}(\propto_i . y_i)}{\sum_{i=1}^{n}\propto_i} \qquad (13.0)$$

where z is the crisp value and can be used for decision making, αi is the fuzzy implication (firing strength) of the ith rule μ(α) is the degree of membership of the ith route value, yi is the consequent of each rule.

6. RESULT DISCUSSION

The parameters used for the prediction of rainfall are: temperature, humidity, dew point, wind speed and pressure. The values of these parameters were arranged as a string separated by comma to form a single record. These records were further normalized and fuzzified to be used to generate the rules used for prediction by the fuzzy logic system.

Table 4 presents a summary of the result from fuzzy logic system. This table consists of firing strength for an acceptable rule, total records column is obtained from 2010 rainfall record data, correctly classified record column shows how many records from the total records were classified correctly and the prediction error of the classification.

Table 4: Fuzzy logic result summary

Firing strength (rule threshold value)	Total records (unclassified records)	Correctly Classified records	Prediction Error (PE) %
40.0	8204	4021	52.13
50.0	8204	5221	34.17
60.0	8204	5802	29.28
70.0	8204	4217	48.60
80.0	8204	4771	41.85
90.0	8204	3866	52.88

From table 4, it can be seen that the firing strength of 60.0 has the minimum prediction error.

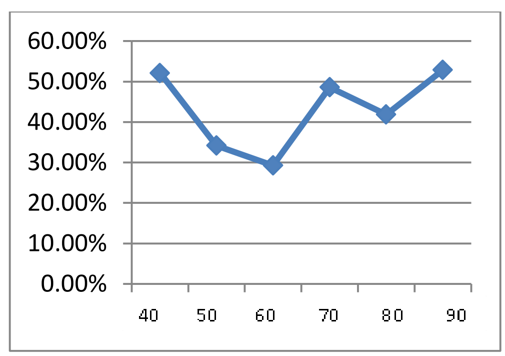

Figure 5: Prediction error against rule firing strength.

The value of the firing strength of 60.0 was used to generate the rules that were used to classify the values in table 5, which presents the rainfall condition and the results of the FL predicted value from the actual value.

Table 5: Actual Values versus Predicted Values

Rainfall Condition	Fuzzy Logic	
	Actual	Predicted
Very low RF	8162	8093
Low RF	29	22
Medium RF	9	5

High RF	1	0
Very High RF	3	2

Finally, the observed data and predicted data were plotted. The results showed that FIS model is promising and efficient and can successfully predict the amount of the rainfall.

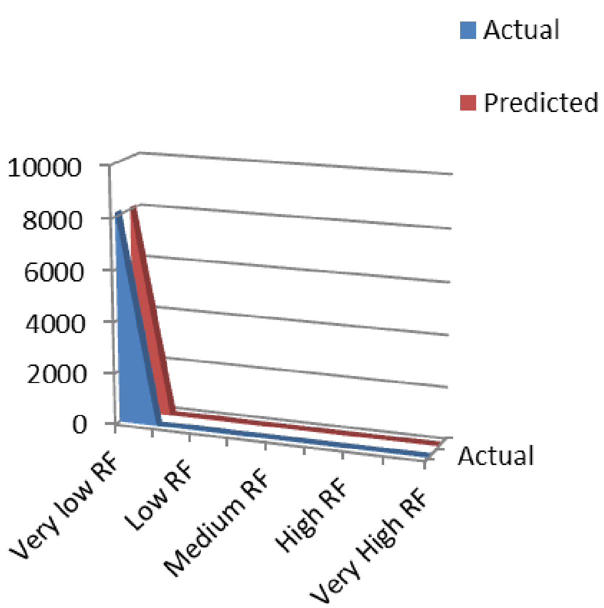

Fig 6: Actual Values versus Predicted Values

7. ERROR MEASURES

The following error measures were calculated to ascertain the efficiency of the fuzzy rule-based model.

7.1 Prediction Error $(PE) =$

$$\frac{\langle |y_{predicted} - y_{actual}| \rangle}{\langle y_{actual} \rangle} \qquad (14.0)$$

The predictive model is identified as a good one if the PE is sufficiently small i.e. close to 0.

7.2 Root Mean Square Error (RMSE)

is a good measure of prediction accuracy. It is frequently used to measure the differences between values predicted by a model and the values actually observed from the thing being modeled. These individual differences are also called residuals.

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_j^N (y_j - \hat{y}_j)^2}{N}} \qquad (15.0)$$

where y_j are observed values, $\hat{y}_j$ are predicted values for rainfall and N is the number of observation.

7.3 Mean Absolute Error (MAE)

the smaller the MAE, the better the model fit.

$$\boldsymbol{MAE} = \frac{|y_j - \hat{y}_j|}{N} \qquad (16.0)$$

where y_j are observed values, $\hat{y}_j$ are predicted values for rainfall and N is the number of observation.

$$\boldsymbol{Accuracy} = 100 - RMSE \qquad (17.0)$$

Table 6: Calculated Error Measures

FUZZY LOGIC				
MSE (mm/h)	RMSE (mm/h)	MAE (mm/h)	PE	ACCURACY (%)
965.6	31.074	16.4	0.00999	68.926

8. CONCLUSION

In this study, we attempted to forecast the rainfall based on Fuzzy Inference System technique. As evident from Table 5, there have been few deviations of the predicted rainfall value from the actual. The performance evaluation of the Fuzzy Logic model was done by calculating Prediction error (PE), Root Mean Square Error (RMSE); Mean Absolute Error (MAE), and prediction accuracy. As the PE, RMSE, MAE values on data were comparatively less, the prediction model is reliable and efficient and can be used for rainfall prediction.

9. FUTURE WORK

The Fuzzy Logic technique could be improved upon by combining it with another method i.e., Artificial Neural Network and Genetic Algorithm for its optimization purpose. Also the Fuzzy Inference System could be further improved on by using larger data sets and more rainfall parameters.

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